

Sains Malaysiana 47(2)(2018): 419-426
<http://dx.doi.org/10.17576/jsm-2018-4702-25>

Load Forecasting using Combination Model of Multiple Linear Regression with Neural Network for Malaysian City

(Peramalan Beban Menggunakan Model Gabungan bagi Regresi Linear Berganda dengan Rangkaian Neuron untuk Bandaraya di Malaysia)

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ABSTRACT

Forecasting a multiple seasonal data is differ from a usual seasonal data since it contains more than one cycle in a data. Multiple linear regression (MLR) models have been used widely in load forecasting because of its usefulness in the forecast a linear relationship with other factors but MLR has a disadvantage of having difficulties in modelling a nonlinear relationship between the variables and influencing factors. Neural network (NN) model, on the other hand, is a good model for modelling a nonlinear data. Therefore, in this study, a combination of MLR and NN models has proposed this combination to overcome the problem. This hybrid model is then compared with MLR and NN models to see the performance of the hybrid model. RMSE is used as a performance indicator and a proposed graphical error plot is introduce to see the error graphically. From the result obtained this model gives a better forecast compare to the other two models.

Keywords: Error plot; hybrid model; neural network; regression model; residuals

ABSTRAK

Peramalan berganda data bermusim adalah berbeza daripada peramalan data bermusim biasa kerana ia mengandungi lebih daripada satu kitaran dalam satu data. Model berganda regresi linear (MLR) telah digunakan secara meluas dalam ramalan beban kerana kegunaannya dalam meramalkan hubungan linear dengan faktor lain tetapi MLR mempunyai kelemahan iaitu mempunyai kesukaran dalam memodelkan hubungan linear antara pemboleh ubah dan faktor yang mempengaruhi. Model rangkaian neural (NN) di sisi lain, adalah model yang baik dalam pemodelan data linear. Oleh itu, dalam kajian ini gabungan MLR dan NN model dicadangkan gabungan ini untuk mengatasi masalah tersebut. Model hibrid ini kemudiannya dibandingkan dengan MLR dan NN model untuk melihat prestasi model hibrid. RMSE digunakan sebagai penunjuk prestasi dan plot ralat grafik diperkenalkan untuk melihat ralat secara grafik. Daripada keputusan yang diperoleh model ini memberikan ramalan yang lebih baik berbanding dengan dua model yang lain.

Kata kunci: Model hibrid; model regresi; plot ralat; rangkaian neural; sisa

INTRODUCTION

Modelling a load forecasting is a very important task for electricity to function in a more efficient and safety way, give the most optimum cost for cost saving applications relying on operating reconstruction (Hahn et al. 2009; Soares & Medeiros 2008). By predicting the future load demands, power system planners and demand controllers could ensure that they would be enough supply of electricity to cope with increasing demands (Mastorocostas et al. 2000). For these reasons, load forecasting has attracted not only researchers but also organisation with same interest to forecast energy usage by using various methods from classical methods to the advanced methods.

Forecasting seasonal load demand has become increasingly challenging in recent period. Classical methods such as regression, holt winter's and exponential smoothing are suitable for a large number of series, for

analyst with limited skill and also for a norm of comparison It follows certain pattern which was determined by the parameter of the model. But it is common for load data to contain a seasonal pattern. Because of these reasons, new models such as artificial neural network and fuzzy time series have been developed in order to find a better and accurate forecast for load forecasting (Chatfield 2005).

Modeling multiple seasonal loads is no longer optimal with standard seasonal methods. Multiple seasonal cycles is differ from the usual seasonal time series. In multiple seasonal cycles, it can contain two or more cycles. Malaysian data contain both daily and weekly cycles. Malaysia has many public holidays because of the ethnicity variation. The cycles from Monday to Friday are similar and Saturday and Sunday are quite discrete. And the patterns for public holidays are quite similar to weekends compare to weekdays. And as stated by Gould et al. (2008), the levels of the daily cycles may change from one week

to the next and yet it still highly correlated with the prior levels of the next day.

A simple or singular method can lead to a bias or inaccurate forecast (Basheer et al. 2014). Thus, a few research teams such as Basheer Shukur et al. (2014) and Mohamed and Ahmad (2010) have developed a hybrid model to deal with this double cycle problem. Some have also used a double seasonal ARIMA to overcome double seasonal difficulties (Mohamed et al. 2011, 2010). Dudek (2016) proposed a linear regression model with patterns of daily cycle. The daily cycle is used as both input and output variables to eliminate the trend and seasonal cycles. Based on the results, the proposed method gives better outcomes compared to the ARIMA, exponential smoothing, neural network and Nadaraya-Watson estimator models.

Ringwood et al. (2001), Taylor (2003), Xiaojuan et al. (2010) and Zhang et al. (2008), even though they advocate the usage of the single model whether the advanced or traditional one, they have also suggested in their further works to consider a hybrid technique because it could improve the outcomes. This method is also being promoted by other researchers like Ying and Pan (2008) and Jang (1993). In this study, a hybrid model combination of multiple linear regression model and neural network will be considered.

The idea of developing this hybrid model comes from Zhang (2003). As mentioned by him, a real data never really consist from pure linear or nonlinear but always contain both linear and nonlinear. Often residuals are being neglected from being considered in analysis. Residuals are important in order to check whether a model is able to fit with a data. Although there is no general statistical diagnostic on how to detect nonlinear autocorrelation relationship but residuals can be concluded in a diagnosis to ensure that both linear and nonlinear part is consider (Zhang 2003). But all in all, the aim is to find a method that can yield a low error for the combined forecasts (Bates & Granger 1969) and the choices of appropriate method is depend on the context, the objectives, the analyst's skill, data characteristics and the number of series to be forecast (Chatfield 2000).

The Holt-Winters method is widely used in practice. It has the advantage of being simple (Chakhchoukh et al. 2011) as it easily copes with trends and seasonal variation (Chatfield 1978). Holt Winter's or multiple linear regression are suitable for a large number of series, given an analyst with limited skill and also for a norm of comparison (Chatfield 2000). It is appropriate to use when parameters stay persistent over time (Bowerman et al. 2005). It is also useful to explore the factors that influence the unusual fluctuations of the data (Ismail et al. 2008). Regression models are widely used for electricity load forecasting. Load is represented by a linear combination of variables related to the weather factors, day type, and customer class (Kyriakides & Polycarpou 2007). It is also appropriate to forecast time series with trend and seasonal factors as they may change over time (Bowerman et al. 2005). Multiple linear regression (MLR) assumes that a regression model employ more than one

independent variable. In regression model, load data will be represented as a linear combination of variables related to other factors and in this study it is the day type (Kyriakides & Polycarpou 2007). But regression model often suffer from a number of difficulty due to a nonlinear relationship between load demand and the influencing factors (Kyriakides & Polycarpou 2007).

Since neural network is a flexible model in modeling a nonlinear data, it will be used to analyse the residuals that will be obtained from the MLR model. Neural network has the competence and accessibility in estimated nonlinear data. It captures some of the key properties which replicate the models of biological neurons works (Bates & Granger 1969; Jang 1993; Kyriakides & Polycarpou 2007; Ringwood et al. 2001; Taylor, 2003; Xiaojuan et al. 2010; Ying & Pan 2008; Zhang 2003; Zhang et al. 2008). Due to this issue, a combination with neural network (NN) is considered in order to enhance the forecast.

METHODS

The idea of the hybrid model came from Zhang (2003). In this study, a hybrid model combination of two models together. The first model will be used to forecast the output data and the second model will be used to forecast the residuals output from the first model. MLR model is selected because of the suitability in modelling a consistent parameter over time. In this case, the parameters will be the days since the data have been arranged into 24 sets of independent series of data. Neural network will be combined with MLR model because of its benefit in modelling a nonlinear data. As being stated by Zhang (2003), the relationship between an actual value and a forecasting can be written as:

$$y_t = \hat{y}_t + \varepsilon_t \quad (1)$$

where y_t is the actual value, \hat{y}_t is the forecasted value and ε_t is the error or residual. From this equation, the \hat{y}_t will be calculated by using MLR model and the error term or residual, ε_t will be forecast by using NN model.

MLR model employ more than one independent variable. The linear regression model relating y to x_1, x_2, K, x_k is:

$$y = \mu_{y|x_1, x_2, K, x_k} + \varepsilon = \beta_0 + \beta_1 x_1 + L + \beta_k x_k + \varepsilon, \quad (2)$$

where $\mu_{y|x_1, x_2, K, x_k} = \beta_0 + \beta_1 x_1 + L + \beta_k x_k$ is the mean value of the dependent variable y when the values of the independent variables are x_1, x_2, K, x_k . $\beta_0 + \beta_1 + L + \beta_k$ are (unknown) regression parameters relating the mean value of y to x_1, x_2, K, x_k . ε is the error term that describes the effects on y of all factors other than the values of the independent variables x_1, x_2, K, x_k .

In this study the linear regression model can be written as:

$$y = \mu_{y|x_1, x_2, K, x_7} + \varepsilon = \beta_0 + \beta_1 x_1 + L + \beta_7 x_7 + \varepsilon, \quad (3)$$

where x_1, x_2, K, x_7 are dummy variables where x_1 is Monday, x_2 is Tuesday and so on since the data used in this study is a daily recorded data. After data is analysed with

MLR, the residuals obtained from the in-sample forecast of MLR will be analysed by using neural network in Matlab software. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons will be used in the neural network process. The network will be trained with Levenberg-Marquardt backpropagation algorithm and if there is not enough memory, scaled conjugate gradient backpropagation will be used to train the network. The step by step process of the process can be written as follows:

First step: Data is modelled by using the MLR model. *Second step:* Residual obtained from the in-sample forecast is calculated and the ACF and PACF of the residuals are plotted to find the lags. If the lags are not stationary, then the residuals will be difference to 1 to make the ACF and PACF lags stationary. The lags obtained will be used as the input nodes that will be used in the next process. *Third step:* Neural network model is then used to model the out-sample forecast of the residual. *Forth step:* The final out-sample forecast is obtained by adding the out-sample forecast from the MLR model with the out-sample forecast of the residuals obtained from the neural network modelling process.

The results of the point estimated for the parameters are listed in the Table 1 below. The parameters x_1 represent Monday, x_2 represents Tuesday and so on until x_7 represent Sunday. The parameters estimation of the MLR model can be written as:

For example, we could write the equation of the MLR model of 6 am as:

$$y = 25098 + 8.0x_1 + 8.5x_2 + 8.5x_3 + 8.2x_4 + 4.3x_5 + 2.4x_6 + 6.8x_7 \tag{4}$$

The input lags in neural networks are determined based on autoregressive (AR) term in Box-Jenkins model. Park et al. (1996), Tang and Fishwick (1993) and Zhang and Qi (2005) suggested that lags can be determined by the AR terms and ignoring the MA terms. Based on the ACF and PACF plots of the residuals, the best Box-Jenkins model is

either ARIMA(0,1,1) or ARIMA(2,1,1) or ARIMA(2,1,2). The model for ARIMA(0,1,1) can be written as:

$$\begin{aligned} (1 - B)y_t &= (1 - \hat{\theta}B)a_t \\ y_t - y_{t-1} &= a_t - \hat{\theta}a_{t-1} \\ y_t &= y_{t-1} + a_t - \hat{\theta}a_{t-1}, \end{aligned} \tag{5}$$

and for ARIMA(2,1,1) can be written as:

$$\begin{aligned} (1 - B)y_t &= (1 - \hat{\theta}B - \hat{\theta}B^2)a_t \\ y_t - y_{t-1} &= a_t - \hat{\theta}a_{t-1} - \hat{\theta}a_{t-2} \\ y_t &= y_{t-1} + a_t - \hat{\theta}a_{t-1} - \hat{\theta}a_{t-2}, \end{aligned} \tag{5}$$

and for ARIMA(2,1,2) can be written as:

$$\begin{aligned} (1 - B - B^2)y_t &= (1 - \hat{\theta}B - \hat{\theta}B^2)a_t \\ y_t - y_{t-1} - y_{t-2} &= a_t - \hat{\theta}a_{t-1} - \hat{\theta}a_{t-2} \\ y_t &= y_{t-1} + y_{t-2} + a_t - \hat{\theta}a_{t-1} - \hat{\theta}a_{t-2}. \end{aligned} \tag{5}$$

Since only the AR terms need to be considered to choose the input lags, by ignoring the term in (4), the input lags to be considered are lag 1 and for (5) and (6), the input lags are 1 and 2. The input lags will be used to forecast the out-sample of the residuals of the NN model.

The number of neuron could influence the performance of MLP forecast performance. However, using minimum number of neuron is most recommended (Masters 1993). Each neuron is processing unit that used logistic function to calculate the linear combination of inputs. The number of the nodes in the hidden layer could be decrease or increase based on the performance of the network training. In this study, the number of neurons that used is one up to five neurons. But in this study only the one that show the best performance will be discussed and only out-sample forecast is consider since the proposed method only appropriate for the out-sample forecast. For the proposed model, the step by step diagram on how the model working is shown in Figure 1 below.

This method is done by using Minitab and Matlab program. The MLR modeling part is done by using the Minitab software while the NN modeling part is done by using Matlab software.

TABLE 1. Parameters estimation for multiple linear regression model

Coefficient	Constant	x_1	x_2	x_3	x_4	x_5	x_6	x_7
6 am	25098	8.0	8.5	8.5	8.2	4.3	2.4	6.8
12 pm	51470	17.7	18.4	18.1	15.5	-1.9	-10.3	16.7
6 pm	40033	15.4	15.4	15.2	14.3	10.2	6.8	13.9
12 am	25402	7.8	7.9	7.8	7.7	7.7	5.2	6.9

TABLE 2. Input lags for number of nodes in NN

Hour	ARIMA model	Lags
6 am	(2,1,2)	1,2
12 pm	(0,1,1)	1
6 pm	(2,1,1)	1
12 am	(0,1,1)	1

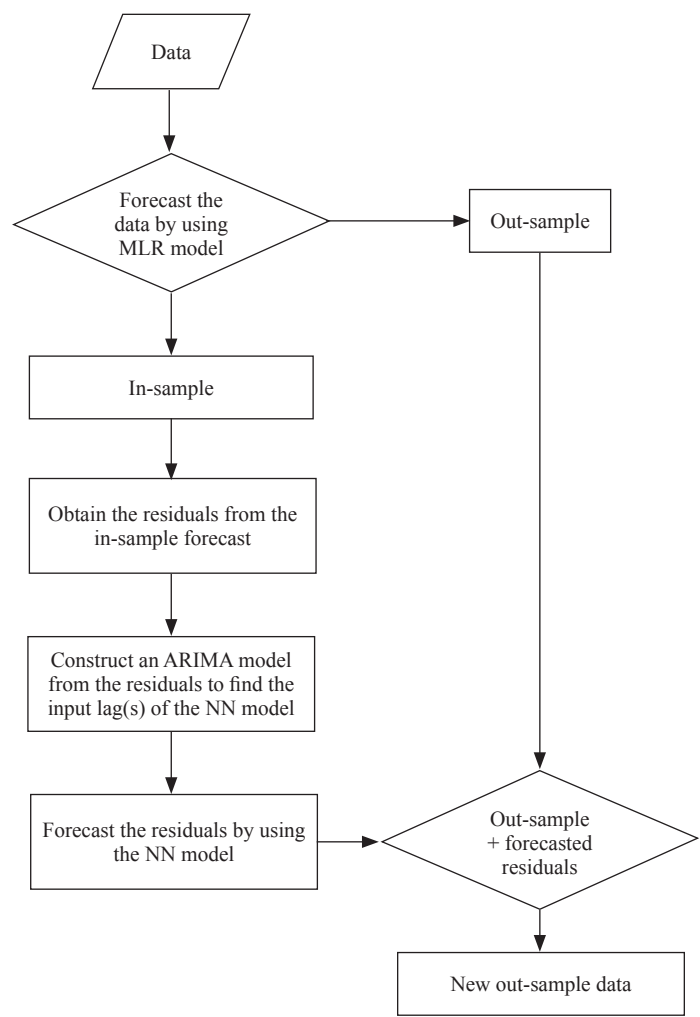


FIGURE 1. Process of how the proposed method performs the forecast

GOODNESS-OF-FIT TESTS

Root mean square error (RMSE) is used as the performance indicator in order to see the performance of the model other than the comparison plot to observe the goodness-of-fit of the hybrid model. The smaller the number of the RMSE indicates the better the model is. RMSE is preferred compare to MSE because of their theoretical relevance in statistical modelling. Often, the RMSE is preferred to the MSE as it is on the same scale as the data (Hyndman & Koehler 2006). The formula of the RMSE can be seen as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2}, \tag{8}$$

where \hat{y}_t is the predicted value and y_t is the observed value. Other than RMSE, we also suggested an error plot in order to compare the results and to determine whether a hybrid model should be considered or not. Usually, plot of error or residual plot is used to see the error graphically. But the problem with residual plot is that it depends on the value from the data. If the data has large number, then the number error could also give a big value which will affect the point in the residual plot. The proposed plot will transform the value of data into percentage by using the formula in order to standardize the value.

$$x_t = \left| \frac{y_t - \hat{y}_t}{y_t} \right|, \tag{9}$$

x_t is the percentage value that will be used in the plot and the value will be between 0 and 1, y_t is the actual value and \hat{y}_t is the forecast value. Since the data is in thousand kilowatt, the error given by RMSE will give a large value. To support the number from RMSE, the MAPE is also used because MAPE will give value in percentage which is more understood where the highest value will be 1 and smallest will be 0. The MAPE is given by this formula:

$$\frac{1}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right|, \tag{10}$$

where y_t is the actual value and \hat{y}_t is the predicted value. For all of the above three performance indicators, the smaller the value and the closer it is to zero, the better is the predicted model in fitting the observed data. Note that the values cannot be negative, since all of the formulas use the modulus or square of the values.

THE DATA SET

We used a data from Tenaga Nasional Berhad Johor Bahru. Data were recorded every day for 3 years from a station

named Pusat Bandar Johor Bahru. Pusat Bandar Johor Bahru (PBJB) is a commercial area in Johor Bahru. Four selected hours used in this paper are 6 am, 12 pm, 6 pm and 12 am. These four selected hours represent the peak hours and the dip hour in Johor Bahru and generally it can represent the daily scenario in Malaysia too.

For casual hours like 6 am and 12 am, there are not much differences of load usage between weekdays and weekends but for peak hours such as 12 pm and 6 pm the load usage during weekdays is higher compare to the weekend's usage. These four hours are selected not only because of the high and low usage, but also to see the pattern and differences of the load usage between these hours.

RESULT AND DISCUSSION

A comparison between residual plot and percentage error plot is discussed here. As can be seen from Figure 2,

residual plot do not have a fix scale on the y-axis. The scale on the y-axis depends on the value of the residual. Therefore, there is not much information gained from this plot. Compare to percentage error plot, the scale on the y-axis is fixed from 0 to 1. It is easier to determine whether the forecast is good or not. And one can set its own benchmark when making a decision to determine a good or bad forecast.

Other than using the percentage error plot as a comparison between models, it also could be used as a benchmark plot for certain purpose. In this study, we used this plot to determine whether a data need to be forecasted with hybrid or not. We set the benchmark at 0.4. If there is any point exceeds 0.4, a hybrid model will be considered. As can be seen from the figures below, 12 pm and 6 pm contain points which is greater than 0.4. To ensure that this rule could be applied, we test all of the data used in this study with the proposed hybrid model and compare it with the result in RMSE.

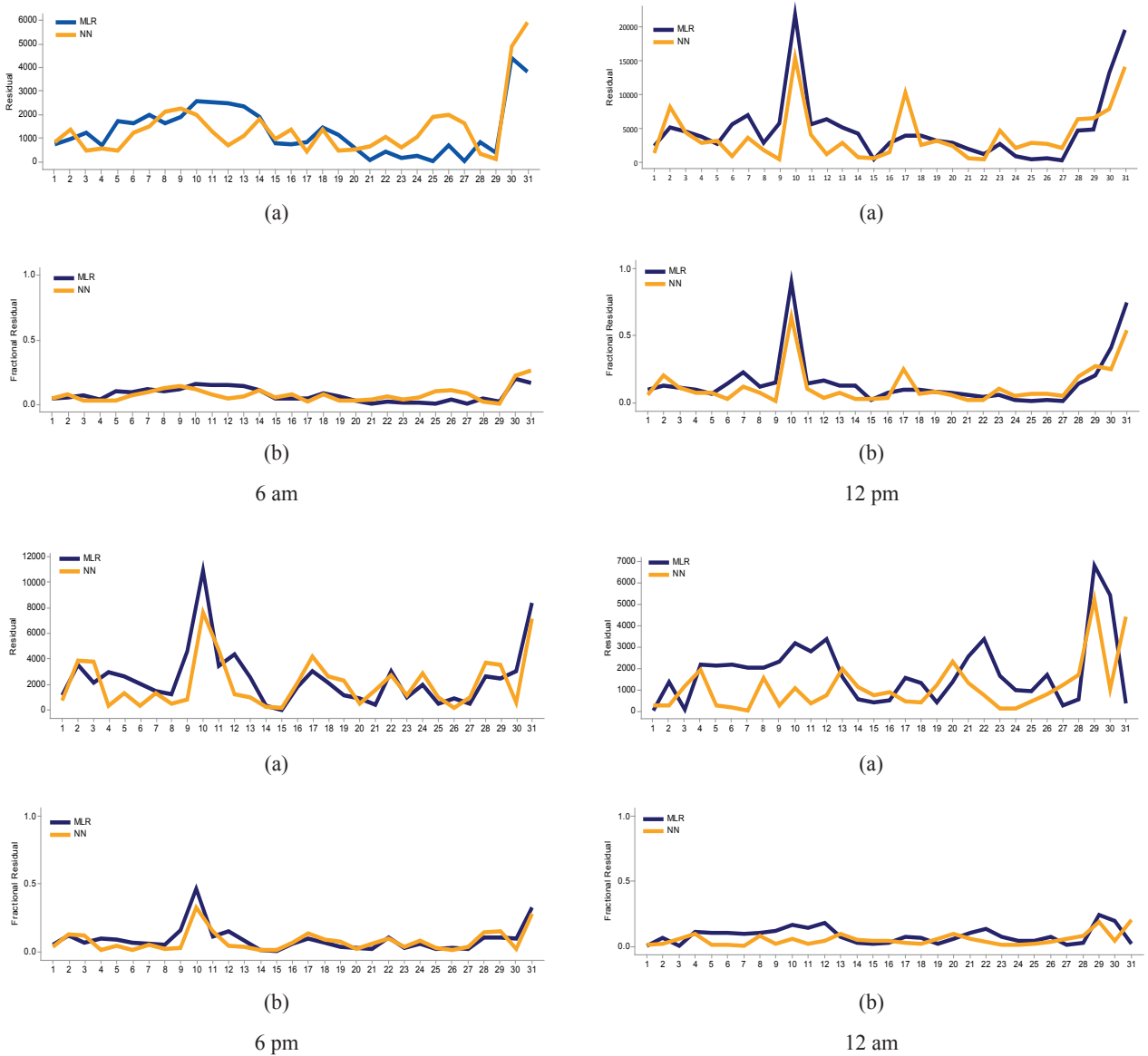


FIGURE 2. A comparisons between residual plot (a) and fractional residual plot (b) for selected times

Here is the result of the hybrid model. 6 am, 12 pm, 6 pm and 12 am from Pusat Bandar Johor Bahru was selected for this purpose. Comparing the plots of percentage error above and the error measurement in Table 3 below, it is agreed that for 12 pm and 6 pm where there are points that exceed 0.4, hybrid model gives smaller value of RMSE and for 12 am where all the points are below 0.4 in the plot, NN shows smaller value of RMSE compare to hybrid model which suggest that hybrid model is not necessary.

As for 6 am, although all the points in the plot are below 0.4, hybrid model shows a smaller value of RMSE. This is understood since 6 am represent the transition time when most people in Malaysia start their day. At this hour, they usually busy preparing their self to working and other activities. Therefore, transition hour should be considered to be tested with hybrid model. The result of the out-sample forecast can be seen in the figures and tables below. Other than that, absolute error plot also shows that all forecast by using NN gives small error which could also suggest that it is a good model if hybrid model is not used for this data.

The result of the out-sample for selected hours can be seen in Table 3. Both tests show consistent results for the models of selected hours. For 6 am, 12 pm and 6 pm, the hybrid model gives a better result compare to other models. The RMSE for 6 am was reduce to almost 41.3% while when data is forecasted with the hybrid model compare to MLR and 46.1% was reduce for RMSE compare to NN model. The RMSE for 12 pm reduce to almost 35.5% compare to MLR and reduce 17.1% compared to NN model. As for 6 pm, the hybrid model also fit the data well compare to MLR and NN. A reduction in RMSE result can be seen from Table 3. Other than using the absolute error plot as a comparison between models, it also could be used as a benchmark plot for certain purpose. In this study, we used this plot to determine whether a data need to be forecasted with hybrid or not. We set the benchmark at 0.4. If there is

any point exceeds 0.4, a hybrid model will be considered. As can be seen from the figures below, 12 pm and 6 pm contain points which is greater than 0.4. To make sure that this rule could be applied, we test all of the data used in this study with the proposed hybrid model and compare it with the result in RMSE.

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The MAPE shows a consistent result as the RMSE. For hour 6 am, 12 pm and 6 pm, the hybrid model shows the smallest value of RMSE and MAPE which indicate that the model is the best compare to MLR and NN models. Hour 12 am shows that NN with neuron 5 is slightly better compare to hybrid model but from MAPE we could see that the difference is only 0.001. Thus, from the error measurements results we could see that the hybrid model did improve the forecast of the load data. The more obvious pattern can be seen in figures below.

As can be seen from Figure 3, the outline of hybrid plot is closer to the actual plot outline compare to the other two plots. Although at certain point, the hybrid model could not detect the actual point, but as can be seen at point 31 in x-axis where there is a sudden increment in the load usage reading, the hybrid did follow the actual value pattern compare to the MLR or NN models. While for 12 pm, the pattern of the load is more obvious where a sudden drop-off could be seen from the plot in Figure 4. This is understand as explained above, 12 pm is the peak hour and the sudden drop-off is actually the weekend when people are mostly not working and since this data cover the urban region, the pattern is obvious at 12 pm compare to the other three hours. From the figures above, it is obvious that the hybrid model gives better performance in following the pattern of the actual load compare to MLR and NN.

Overall, as can be seen from Figures 3-5, NN and hybrid give a quite identical plot and could read the pattern of the actual data. Although at certain time such as 12 am the hybrid model does not gives a good result, it can still be concluded that this hybrid model could be used to forecast the load data especially load data from Malaysia. NN is a good model when forecasting a nonlinear data. As can

TABLE 3. Error measurement of selected hours

Hour	Model	MAPE	RMSE
6 am	MLR	0.073	1679
	NN(4)	0.074	1829
	Hybrid(1)	0.029	986
12 pm	MLR	0.151	6874
	NN(3)	0.115	5346
	Hybrid(5)	0.086	4433
6 pm	MLR	0.087	3344
	NN(5)	0.073	2840
	Hybrid(4)	0.054	2289
12 am	MLR	0.080	2332
	NN(5)	0.049	1599
	Hybrid(2)	0.050	1859

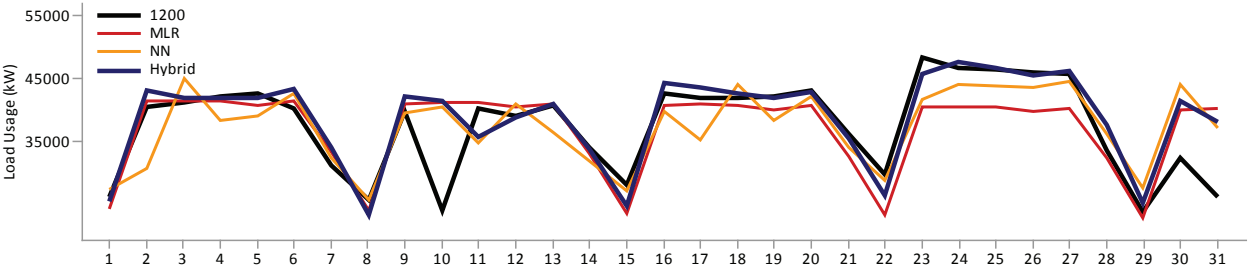


FIGURE 4. Time series plot for 12 pm

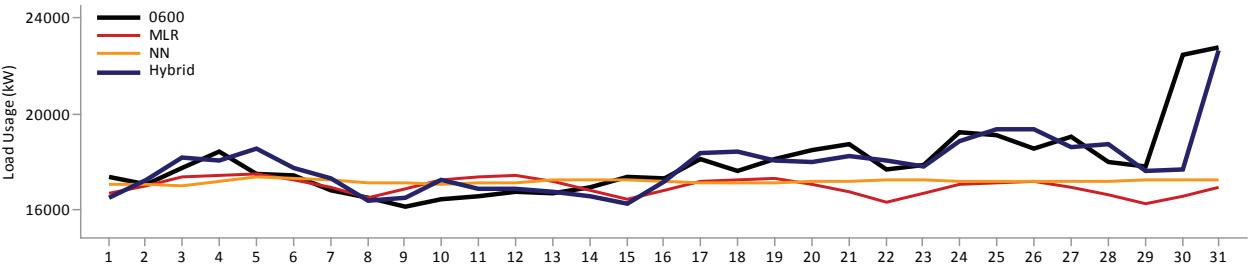


FIGURE 3. Time series plot for 6 am

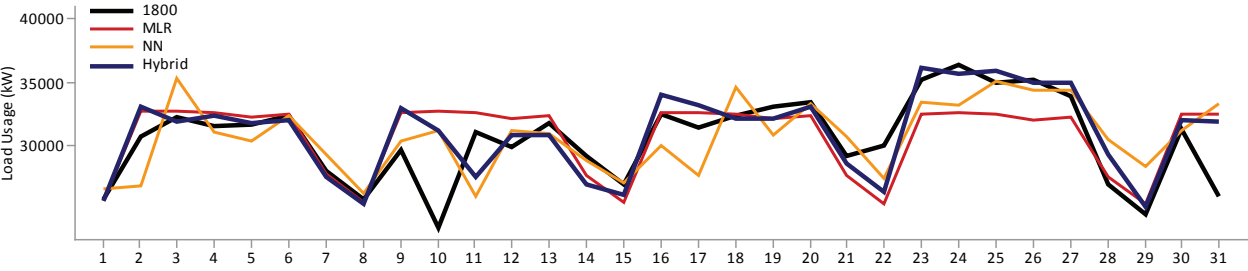


FIGURE 5. Time series plot for 6 pm

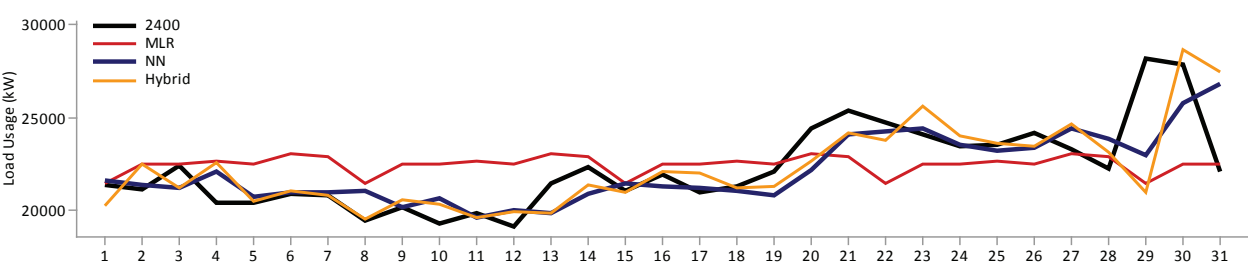


FIGURE 6. Time series plot for 12 am

be seen from Figure 6, the load at 12 am did not show an obvious seasonal pattern compare to the others. Because of that, NN shows a superior result compare to hybrid model for 12 am. However NN is also a good model in forecasting the load compare to the traditional model, MLR. Therefore, if ones do not wish to forecast by using the hybrid model, NN model could be consider as an alternative model.

CONCLUSION

The hybrid model has shown to be superior compare to MLR and NN models. The combination of MLR and NN is a good combination especially for a data that has a similar pattern like Malaysian data. Malaysian data has a multiple seasonal

pattern since the data contain few cycles in the load and since regression can model a data with variable from other factor and NN is a good model in modelling a nonlinear data, the combination of these two models could enhance the forecasting of the load. The percentage error plot is also a good plot to check the error graphically. It could give brief idea on whether a forecast is good or bad and it also can be used to make a comparison between models.

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Received: 1 May 2016

Accepted: 16 August 2017